# CS 886: Multiagent Systems Multiagent Learning 

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## Outline

(1) Introduction

## (2) Repeated Games

(3) Learning in Repeated Games

4 Stochastic Games

## Introduction

- So far we have focused on computing optimal/equilibrium strategies
- Another approach: learn how to play a game
- Play the game many times
- Update your strategy based on experience
- Why?
- Some aspect of the game may be unknown to you
- Other agents may not be playing in equilibrium
- Computing an optimal strategy is hard
- Learning is what people do


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## Challenges

- There are other agents in the environment
- Dynamic environment (true in single agent settings)
- What others are learning depend on what our agent is learning
- Complex global behaviour of the system
- Difficult to separate learning from teaching



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| T | 1,0 | 3,2 |
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## Goals of Multiagent Learning

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## Repeated Games

Typically

- Agents play a normal-form game (the stage game)
- They see what happened (and get the payoffs)
- They play again
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Can be repeated finitely or infinitely

- Extensive-form game with subgame-perfect equilibrium being repetition of some NE of the stage game
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## Finitely-repeated Prisoners' Dilemma

|  | $C$ | $D$ |
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| $C$ | 2,2 | 0,3 |
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\lim _{n \rightarrow \infty} \sum_{1 \leq t \leq n} \frac{u(t)}{n}
$$

- Discounted payoff:

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\sum_{t} \delta^{t} u(t) \text { for some } \delta, 0<\delta<1
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Tit-for-tat strategy:

- Cooperate in first round
- In every later round do the same thing that the other player did in the previous round
Trigger strategy:
- Cooperate as long as everyone cooperates
- Once an agent defects, defect forever

Folk Theorem: Any utility vector can be realized in NE if and
only if it is feasible and enforceable.

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## Fictitious Play

Early and simply learning rule

- Initialize beliefs about opponent's strategy
- Repeat
- Play a best-response to assessed strategy of opponent
- Observe opponent's actual play and update beliefs accordingly

Note that agent is oblivious to the other agent's utilities.

## Properties of Fictitious Play

## Definition

An action profile a is in steady state if whenever a is played in round $t$ then it is played in round $t+1$.

## Theorem

If a pure strategy profile is a strict NE of a stage game, then it is a steady state of fictitious play in the repeated game.

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If the empirical distribution of each agent's strategies converges in fictitious play then it converges to a Nash equilibrium.

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## Regret-based Learning

## Regret:

$$
R_{i}\left(a_{i}, t\right)=\frac{1}{t-1}\left[\sum_{1 \leq t^{\prime} \leq t-1} u_{i}\left(a_{i}, a_{-i, t^{\prime}}\right)-u_{i}\left(a_{i, t^{\prime}}, a_{-i, t^{\prime}}\right)\right]
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An algorithm has zero-regret if or each $a_{i}$, the regret for $a_{i}$ becomes non-positive as $t$ goes to infinity (almost surely) against any opponents

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\sigma_{i}^{t+1}=\frac{R^{t}\left(a_{i}\right)}{\sum_{a^{\prime} \in A_{i}} R^{t}\left(a^{\prime}\right)}
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- If all players use regret matching, then play converges to the set of weak correlated equilibria
- Other types of regret-based learning have different properties


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## Targeted Learning

- Assume that there is a limited set of possible opponents
- Try to do well against these

> Example: is there a learning algorithm that
> (1) Learns to best-respond against any stationary opponent (one that always plays the same mixed strategy), and
> (2) Converges to a Nash equilibrium when playing against a copy of itself (self-play)?

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- Multiple states $S=\left\{S_{1}, \ldots, S_{m}\right\}$
- Each state, $S_{i}$ is a normal form game
- After a round, random transition to another state
- Transition probabilities depend on state and action taken
- Typically discount utilities over time

Note:

- 1-state stochastic game $=($ infinitely $)$ repeated game
- 1-agent stochastic game = Markov Decision Process (MDP)


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- A stationary strategy specifies a mixed strategy for each state
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- An equilibrium in stationary strategies always exists [Fink 64]
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